Higher Education Stakeholders' Views on Guiding the Implementation of Learning Analytics for Study Success

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Learning analytics show promise to support study success in higher education. Hence, they are increasingly adopted in higher education institutions. This study examines higher education stakeholders' views on learning analytics utilisation to support study success. Our main research question was to investigate how ready higher education institutions are to adopt learning analytics. We derived policy guidelines from an international systematic review of the last five years of learning analytics research. Due to the lack of rigorous learning analytics research and adoption, this study examines how ready university stakeholders are to adopt learning analytics. In order to validate the guidelines, we conducted an interview study with 37 higher education stakeholders. The majority of participants stated that their institutions required further resources in order to adopt learning analytics but were able to identify what these resources were in order for successful implementation. Overall, stakeholders agree that learning analytics show much promise to support study success at higher education institutions.

Keywords: Learning analytics; study success; adoption; policy recommendation

Introduction

Learning analytics are increasingly adopted and utilised in higher education institutions in countries such as Australia, UK and the USA (Sclater & Mullan, 2017). Learning analytics are regarded as the use of static and dynamic information about learners and learning environments, assessing, eliciting and analysing it, for real-time modelling, prediction and optimization of learning processes, learning environments, as well as educational decision-making (Ifenthaler, 2015). They are essential data-driven tools, which allow educators to view the learning progress of students so that they can be supported if they are under-achieving or at risk. Learning analytics can also be used to motivate students to stay on their university courses and therefore facilitate and increase study success (Mah & Ifenthaler, 2018). Learning analytics can be descriptive, predictive or prescriptive and offer different ways in which they can be designed, implemented and deployed to facilitate students' learning and their retention on courses (Ferguson et al., 2016; Glick et al., 2019). Learning analytics data for summative reporting are obtained from sources such as course assessments, surveys, student information systems, learning management system activities, and forum interactions by *descriptive analytics* (Arthars et al., 2019). Similar data from those sources and attempts to measure onward learning success or failure are utilised by *predictive analytics* (Glick et al., 2019). Algorithms to predict commonly the study success and whether students retain on their courses as well as suggesting immediate interventions are deployed by *prescriptive analytics* (Baker & Siemens, 2015). Typically, a student profile and their associated learning progress can be viewed, examined and appropriate alerts and/or actions can be taken (Klasen & Ifenthaler, 2019). The benefits of utilising learning analytics in learning environments are a) increasing students' learning (experiences and effectiveness) and their learning motivation (Schumacher & Ifenthaler, 2018), and thereby, reducing student dropout or inactivity and increasing study completion (Chai & Gibson, 2015), and b) providing personalised and/or adaptive learning paths via the specific goals set by the teacher or student to support the learning process (Fuchs, Henning, & Hartmann, 2016). However, the use of learning analytics outside Australia, UK and the USA is still relatively rare (Ferguson et al., 2016; Sclater, Peasgood, & Mullan, 2016).

In order to validate derived guidelines from a systematic review of learning analytics literature (Ifenthaler, Mah, & Yau, 2019), this contribution focusses on the acceptance of the learning analytics tools to increase the study success by higher education stakeholders.

Learning analytics and study success

Study success includes the successful completion of a first degree in higher education to the largest extent, and the successful completion of individual learning tasks to the smallest extent (Sarrico, 2018). As some of the more

common and broader definitions of study success include terms such as retention, persistence, graduation rate and the opposing terms include withdrawal, dropout, non-completion, attrition and failure (Mah, 2016).

Learning analytics show promise to enhance study success in higher education (Pistilli & Arnold, 2010). For example, students often enter higher education academically unprepared and with unrealistic perceptions and expectations of academic competencies for their studies (Mah & Ifenthaler, 2017). Both, the inability to cope with academic requirements as well as unrealistic perceptions and expectations of university life, in particular with regard to academic competencies, are important factors for leaving the institution prior to degree completion (Mah, 2016). However, Sclater and Mullan (2017) reported on the difficulty to isolate the influence of the use of LA, as often they are used in addition to wider initiatives to improve student retention and academic achievement. Still, a number of reports currently exist in the area of LA including policy recommendations, each of which are detailing their individual policy recommendations for their geographical contexts. For example, Colvin et al. (2015, p. 3) provided a set of policy recommendations for the Australian context:

1) "Facilitating broader institutional, cross institutional and government discussions of LA and its capacity to inform sectorial challenges;
2) Developing capacity building initiatives. This may manifest as professional development, secondments, and postgraduate course opportunities;
3) Developing and supporting new models of education leadership that embrace complexity and enables innovation, organizational agility and adaptivity".

Five successful LA implementation-enabling factors in Australia include (Colvin et al., 2015, p. 20): 1) "Higher education leaders coordinate a high-level LA task force; 2) Leverage existing national data and analytics strategies and frameworks; Establish guidelines for privacy and ethics; Promote a coordinated leadership programme to build institutional leadership capacity; Develop an open and shared analytics curriculum (to develop systematic capacity for LA by training skilled professionals and researchers)." A similar set of policy recommendations was provided by Ferguson et al. (2016) in the European context, who also presented a discussion on how some countries such as Australia, Denmark, The Netherlands and Norway have successfully adopted LA. From an integrative review based on five years of research on learning analytics and study success, the following guidelines have been derived (Ifenthaler et al., 2019):

- Developing flexible learning analytics systems which cater for the needs of individual institutions, i.e., their learning culture, requirements of specific study programmes, students and lecturers dispositions, technical and administrative specifications as well as the broader context of the institution.
- Defining requirements for data and algorithms of learning analytics systems.
- Involving all higher education stakeholders in the development of a learning analytics system.
- Establishing organisational, technological and pedagogical structures and process for the application of learning analytics systems as well as providing support for all involved stakeholders for a sustainable operation.
- Informing all stakeholders with regard to ethical issues and data privacy regulations including professional learning opportunities.
- Building a robust quality assurance process focussing on the validity and veracity of learning analytics systems, data, algorithms and interventions.
- Funding of research regarding questions on learning analytics within single institutions, research associations and national schemes.
- Constituting local, regional and national learning analytics committees including stakeholders from science, economy and politics with a focus on adequate development and implementation (and accreditation) of learning analytics systems.

Research questions and methodology

The current study aims to validate learning analytics guidelines for the higher education sector which were derived from the findings of a systematic review (Ifenthaler et al., 2019). The overriding research question is as follows: Do experts of the higher education sector confirm and accept guidelines for the implementation of learning analytics for supporting study success in?

Our structured interview study (Mayring, 2015) was conducted over a period of three months including $N = 37$ participants. We first collected a list of suitable participants; they were all had experience in educational technology and were a professional staff at a higher educational institution. Some of these stakeholders work directly or indirectly with learning analytics and have different degrees of knowledge of learning analytics. The

list was drawn from participants' list from e-learning conferences. Subsequently, we contacted them via email to request whether they were willing to participate in the interview study. The interview study was initiated by a pilot study of six stakeholders from our university and these were conducted face-to-face. The pilot study confirmed the expected comprehension by stakeholders and that the questions would be answered as intended and thus eliminating any ambiguity.

Participants in the main interview series included $N = 31$ stakeholder. The interview was conducted via remote conferencing due to practical reasons given the time and resources constraints. All of the interviews were recorded with the participants' consent and stored securely for later anonymous transcription and analysis. 10 out of 37 participants were female and the age range was from 27 to 60. Their areas of expertise include Information Management (with focus on workplace learning), Business Mathematics/Education, Educational Science, Computer/Data Science, Electronic/Mechanical Engineering, Psychology, and Web Technologies.
The interview was divided into eight sections – 1) Learning culture, 2) Study success, 3) Technology acceptance, 4) Understanding of learning analytics, 5) Current learning analytics projects (if any), 6) Strategies, policies and guidelines, 7) Time and resources, and 8) Demographic information.

The interview transcriptions were analysed using content data analysis and specifically we searched for evidence in the interview transcriptions to support/reject our guidelines based on iteratively created categories (Mayring, 2015). The limitations of this study include the subjective opinions of each participant, which may not represent their institution truly. Two different researchers conducted the interviews due to practical reasons; this may also cause subjectivity by each researcher in the way the questions were posed. The researcher analysing the interview transcripts may also interpret the interviews subjectively according to his/her knowledge in this domain. Coding and analysis of the interviews was realised by the research team, communicating about possible inconsistencies with regard to the research questions and categories using f4/f5 software (https://www.audiotranskription.de).

Results and discussion

Understanding of learning analytics, current projects, barriers to adoption

Most participants could provide an accurate description of what learning analytics constitutes. The following elaborations of a potential definition/description of learning analytics was provided by participants, for example participant IP3:

> "*If you collect enough data, one can probably observe patterns of some things that can be improved. It is a type of data analysis, where one can see some practices, which relate to better results of the students in the end or some practices, which may lead to poorer results. Maybe one can also observe when students have more difficulties with their courses and when they are struggling more with one course more than another. This provides another way to know how the learners are coping in the courses in addition to the normal teaching/learning processes where there is minimum interaction. So one can identify which of the used teaching practices lead to either better or worse results for the students.*"

Still, due to the novelty of learning analytics, there is limited research, or resources dedicated for the implementation of learning analytics systems at higher education. For example, one participant experienced a number of difficulties concerning data protection when attempting to implement a learning analytics system. Most of the mentioned barriers to learning analytics adoption were mostly financial constraints including personnel costs (sufficient and qualified multi-disciplinary staff required to operate the different parts of the learning analytics system, for example, pedagogical staff concerning the learning materials, data protection staff concerning data privacy aspects, IT staff concerning technical implementation and maintenance) and actual software, server and licensing costs for the implementation of the learning analytics system. Most participants mentioned that there were not any learning analytics projects currently operating at their institution. In summary, most participants agreed and emphasised that the first, large obstacle to learning analytics implementation was data protection. The regulations to data protection are very important. For example, students have the rights not to provide directly information on how many hours they spent studying, or indirectly via traces of data left when logging on and off a learning management system. Another obstacle is the workload this creates on members of staff. A concern specified by a participant being "*The more data one collects, the better it would be for the learning analytics. However, it might imply possible administering several surveys and questionnaires during the course and may conflict with the dynamics of the course and some teaching staff may not be willing to do so easily.*" Whilst these two points are seen as obstacles, one participant views it rather as a difficulty that can be navigated and overcome. The difficulties lie also on different levels for example one level is linked strongly with trust which

according to the participant who is a computer scientist emphasized that a) they may not trust as much with other knowing their data as staff/students from students from other disciplines purely because they may have a better understanding about what one can do with the data, and b) trust requires a very social component which some computer scientists do not like/are not social. In order to overcome these issues, some strategies can be put in place such as reinstating that not all students' private data will be collected, only those relevant required and with the students' consent. There are also technical aspects, which include the connection of different systems inclusive of data protection issues, which require technical expertise of IT staff and can be problematic.

Readiness to adopt LA and validation of policy recommendations

We examined the responses to the interview question "How ready is your institution to adopt learning analytics?". Six participants expressed that their institution was ready to adopt learning analytics because their institution currently has learning analytics research projects and possibly a system in place and they may effectively adopt more projects or implement learning analytics in students' existing courses in a relatively straight-forward manner. It is also the case that some of these participants stated that they also have currently the personnel required including a professor, a postdoc and doctoral students in this area of research. The majority of participants ($N = 30$) expressed that there are currently resources required by their institution before they can go ahead and adopt learning analytics. In general, these participants expressed that their institution is mentally ready to adopt learning analytics as the benefits of study success outweigh the costs (West, Heath, & Huijser, 2016). The required resources include staff and technological capabilities. Several participants emphasised the problem that there is a lack of learner's personal data relating to their learning processes, exam grades and so on, which makes predictions very difficult. Due to the strict data protection regulations (e.g., EU-GDPR), this is not allowed and therefore eliminates/decreases the ability for learning analytics systems to make accurate predictions based on students' data. The participant could be understand why the data cannot be made available especially given that the data can be anonymised (Ifenthaler & Schumacher, 2019). A further analysis of responses focussed on the validation of the guidelines for the higher education sector. One participant stressed the importance of learning leadership and role models because learning analytics are still a very new field (Buckingham Shum & McKay, 2018). Experimental 'playgrounds' are required to understand, discuss, debate, test out all learning analytics ideas and put them into practice and learn from these good/bad experiences and studies. It is interesting to note that many of the participants have similar ideas about the advantages and disadvantages of learning analytics implementation and ways to overcome the specific challenges. This implies that current challenges in successful learning analytics implementation are widely known within the higher education sector and research community, hence, a list of protocol can be put together to accommodate the requirements and desires of stakeholders in order to adopt learning analytics.

Conclusion and future work

The implications how to support stakeholders at higher education institutions in utilising learning analytics to support study success are still under-documented (Ifenthaler et al., 2019). Remaining questions for future research are: Will students be able to respond positively and proactively when informed that their learning progress is hindered or inactivated?; Will instructors be able to influence the at-risk students positively so that they will re-engage with the studies? In addition, ethical dimensions regarding descriptive, predictive and prescriptive learning analytics need to be addressed with further empirical studies and linked to study success indicators (West, Huijser, & Heath, 2016). As this research reports qualitative data, the findings are limited with regard to their external validity. Hence, further research is required to build further rigorous findings towards the effects of learning analytics systems for supporting study success. As higher education institutions further adopt analytics systems, pedagogical and psychological advances may help to further inform the design, development and evaluation of learning analytics systems.

Acknowledgements

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